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RETRACTED: Research on standardization of power transformer monitoring and early warning based on multi-source data

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To meet the growing demand for integrated monitoring of complex power grid equipment, it is necessary to improve the situational awareness model of power transformers. The model is expected to assist monitoring personnel in timely identifying transformers with deteriorating trends among massive and discrete monitoring information, and to make responses in advance. However, the current transformer state awareness technology generally has the problem of single data source and poor timeliness, and still requires monitoring personnel to make artificial analysis and prediction in combination with telemetry information, which cannot fully meet the requirements of power grid equipment monitoring. This paper is based on multi-source data fusion technology, through associating and mining transformer alarm information, equipment maintenance records and power transmission and transformation online monitoring data, to extract the dimension features of transformer operation situation assessment. By constructing a multi-layer perceptron model, a transformer state transition model based on the principle of Markov chain is established, which can predict possible defects 2 h in advance and achieve good results, and determine the transformer state early warning index, providing sufficient time for monitoring personnel to deploy transformer operation and maintenance work in advance. Finally, the effectiveness of the method proposed in this paper is proved by the case of transformer crisis state in a city substation, and the method proposed in this paper has important significance for transformer state early warning.

KEYWORDS

power system, power transformer, fault warning, situational awareness, multi-source data

1 Introduction

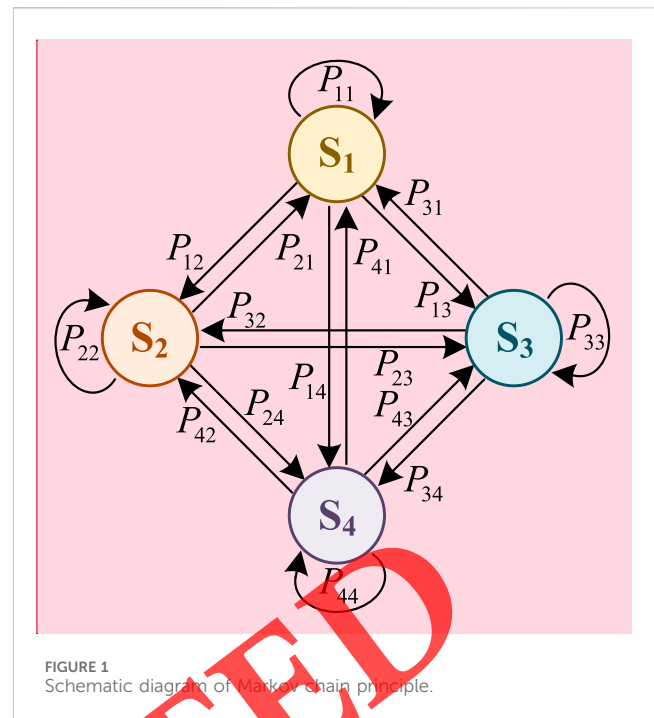
With the rapid development of society and the advancement of informatization of the power grid, the importance of the health status of electrical equipment in the power supply system is gradually becoming more prominent (Ausmus et al., 2019). However, the current massive and discrete electrical data is difficult to intuitively and accurately reflect the actual fault status of the equipment due to the lack of hierarchical or judgmental processing (Soni and Mehta, 2021; Wang et al., 2021). In accordance with the requirements of power regulation and management business, once equipment faults or abnormal information are issued, monitoring personnel must quickly determine the cause of the anomaly based on the

monitoring data. Currently, monitoring personnel still rely heavily on experiential analysis of the relationship between signals and subjectively judge the state of the equipment, lacking the corresponding technical means to intelligently determine potential faults and consequences. It is difficult for them to accurately classify and handle complex faults, multiple faults, and large-scale faults caused by extreme weather conditions in a rapid and effective manner (Trappey et al., 2015; Hou et al., 2021; Wang et al., 2022).

Power transformers, critical monitoring apparatus in substations, generate a wealth of information. However, accurate discernment of their operational status is hindered by several factors. The current transformer state perception model is not yet perfect, primarily relying on state detection analysis results and expert judgment (Mharakurwa, 2022; Horalek and Sobeslav, 2023). Additionally, the construction level of power grid information systems is inconsistent, and the operation and maintenance data of transformer equipment have not been effectively linked and shared, often necessitating manual correlation. Existing systems' multi-source data quality, reflecting the transformer equipment status, is inadequate, particularly with online monitoring data, leading to frequent errors or misjudgments by monitoring personnel (Abbasi, 2022; Enjavimadar and Rastegar, 2022). The precision of fault diagnosis and prediction is unsatisfactory, especially with complex or concurrent faults. The absence of effective data integration and sharing mechanisms among different systems also impedes the full utilization of monitoring data. Moreover, the quality of online monitoring data, vital for accurate fault diagnosis, is often undermined by noise and other disturbances.

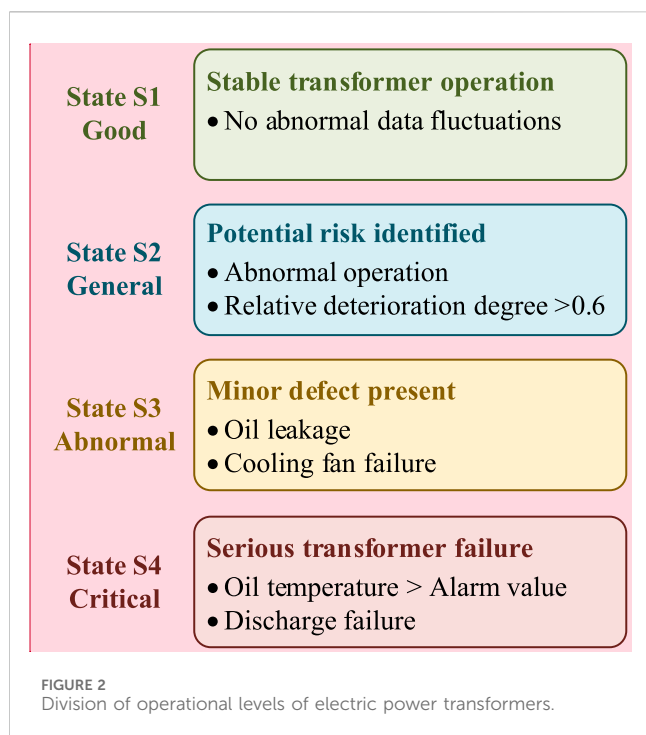
In recent years, many experts and scholars have conducted research on fault warning of power transformers and achieved many results. For example, by establishing the corresponding relationship between transformer fault modes and status parameters in online monitoring, calculating the probability of equipment fault occurrence, and completing a comprehensive evaluation of reliability and operational risk based on transformer state perception (Bai et al., 2021; Fahim et al., 2021; Ravindran et al., 2021; Zhang et al., 2023). Literature (Prasojo et al., 2023) realized transformer fault diagnosis by combining synthetic minority class oversampling technique and random forest. Literature (Zhang C. et al., 2020) proposes a power transformer fault diagnosis method based on domain knowledge graph and improved graph convolution network, constructs a power transformer knowledge graph composed of nodes and edges, and establishes the mapping relationship between the knowledge graph and fault samples to form the transformer fault knowledge graph. Literature (Yao et al., 2020) Based on voiceprint feature recognition technology, the operation and maintenance detection method of power transformer is studied. With the development of big data technology, big data analysis technology has also been gradually applied to the assessment of transformer status (Gashteroodkhani et al., 2020; Mitiche et al., 2021).

In the field of fault diagnosis and maintenance of transformers, existing work includes the following. Jia et al. (2023) in paper, proposed a novel non-destructive testing method for the dielectric loss factor based on multi-frequency ultrasound technology and artificial neural networks. By using an Elman neural network optimized with Kernel Principal Component Analysis (KPCA) and Whale Optimization Algorithm (WOA), this method can effectively predict the quality of transformer oil. Peng et al.



(2023) in paper, analyzed the adsorption and sensing behavior of Ru3-SnS2 on four typical dissolved gases in insulating oil (H_2 , CO , C_2H_2 , C_2H_4) using Density Functional Theory (DFT), providing theoretical guidance for the application of Ru3-SnS2 under operating conditions of oil-immersed transformers. Li et al. (2022) in paper, proposed a new transformer oil dielectric loss factor detection method based on multi-frequency ultrasound and Particle Swarm Optimization-Elman Neural Network (PSO-ENN) predictive model, laying a foundation for the development of online monitoring systems. Tang et al. (2020) in paper, achieved qualitative identification and quantitative analysis of fault characteristic gases in oil-immersed transformers in a mixed atmosphere using a MEMS sensor array and DBN-DNN pattern recognition method. Huang et al. (2023) in paper, analyzed the potential of Pt-doped HfS2 monolayer as a gas-sensitive material for detecting dissolved gases in oil (H_2 , CO_2 , CH_4 , and C_2H_2) using Density Functional Theory (DFT), providing theoretical guidance for exploring the application potential of Pt-HfS2 in fault diagnosis and predictive maintenance of oil-immersed transformers. These recent research advancements showcase the potential of various methods and technologies in enhancing prediction accuracy and reliability.

In response to the shortcomings of existing research, this article summarizes the monitoring information of multiple types of transformer equipment, including alarms, defect records, maintenance, testing, and online monitoring of power transmission and transformation. It introduces multi-source data fusion technology and extracts three dimensional features for transformer operation situation assessment. On this basis, a transformer operation situation awareness model based on Markov chain theory was established, and a probability output model for the occurrence of multi class transformer defects was constructed, thereby obtaining a transformer state transition model based on Markov chain principle. The experimental results show



that the model can predict potential defects in transformers 2 h in advance and achieve good prediction results, providing sufficient time for monitoring personnel to deploy transformer operation and maintenance work in advance.

2 Transformer operation situation transfer model based on Markov chain

2.1 Markov chain principle

Markov chain is a stochastic process in state space that undergoes a transition from one state to another, with the probability distribution of the next state determined solely by the current state (Tao et al., 2021). The system can transition from one state to another or maintain the current state at every moment in the Markov chain based on probability distribution. The change in state is called state transition, and the probability of maintaining or transitioning to another state is called transition probability. For example, in Figure 1, P_{ij} shows the transition probability of state i transitioning to state j in the Markov transition process.

The core principle of Markov chain is that the probability distribution of the next state is determined solely by the current state, and is independent of past states. In the model of transformer operating state transition, we regard various possible states of the transformer as states in the Markov chain. Then, based on historical data, we determine the transition probability of transformer states. In this way, we can construct a Markov chain model to describe how the operating state of the transformer changes over time. Based on the description in the previous section, we define the operating states of the transformer as S1–S4. The definition of each state should be based on actual operating parameters, such as active power, reactive power, current, and load rate, etc. The transition between states is

based on certain probabilities. For example, the transition probability from the normal operating state (S1) to the mild fault state (S2) can be statistically calculated through historical data. In this way, we can not only describe how the operating state of the transformer changes over time, but also predict the probability of faults, thereby formulating more effective maintenance strategies.

2.2 Transformer operation situation transfer model

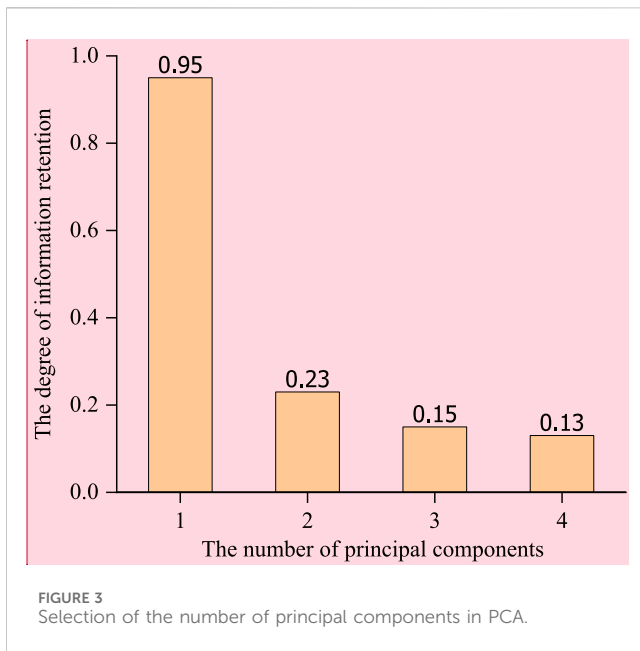
Transformer operation situation refers to the state development trend during transformer operation. With the passage of time, power transformers due to their own materials aging, changes in operating conditions and other factors, its operating situation is bound to gradually decline. In this paper, the transformer operation situation is divided into four categories, namely: good (S1), general (S2), abnormal (S3), critical (S4). The schematic diagram of the division is shown in Figure 2, with specific details as follows:

- (1) State S1: There is no abnormal fluctuation in transformer operation data and online monitoring data.
- (2) State S2: On the basis of considering aging analysis factors such as operating years, if there are abnormal causes in the operation of the transformer, or if the relative deterioration degree of a certain evaluation dimension is greater than 0.6 under the consideration of operating years, operating environment and other characteristics, it is considered that the transformer at this time needs to be paid certain attention by monitoring personnel.
- (3) State S3: The transformer has a small defect that does not affect the normal operation, such as oil leakage, cooling fan failure, etc.
- (4) State S4: The transformer has a serious failure, such as oil temperature above the alarm value, discharge failure, etc.

3 Dimensions of transformer operation situation assessment

3.1 Transformer operation data feature extraction

Transformer operation data can effectively characterize its state changes, such as operating load, overload conditions, abnormal current, and temperature rise. This article adopts a data-driven approach to establish an association between the electrical operation data characteristics of transformers and their operating status. By transforming the time series data of transformer electrical monitoring into supervised learning form and using it as the input layer for model training, a fault time series prediction method based on Long Short Term Memory (LSTM) recurrent neural network is proposed. Through the sigmoid function, the predicted transformer defect feature values of the model are output. Introducing the Attention mechanism into the algorithm model ensures selective learning of the input sequence and the correlation between the output sequence and the input by preserving the intermediate output results of the LSTM encoder. The input



layer of the model includes dimensionality reduction measurement data, oil temperature monitoring data, external meteorological data, transformer anomaly triggering characteristics, and labeling of adjacent circuit breaker actions or connected bus voltage limit exceeding alarm data.

3.1.1 Dimension reduction of transformer measurement data

Due to the actual work of transformers, the current, power and load rate in the measurement data are often highly correlated, and there is a strong correlation between the two, and taking them directly as the model input will produce redundancy. Therefore, by using the Principal Component Analysis (PCA) to select the part with more information instead of the original variable to effectively extract the independent change information of each monitoring quantity. Principal Component Analysis can effectively handle high-dimensional data, extract key information, and reduce the dimensionality of the data. Translate the four monitoring quantities into mutually orthogonal abstract feature quantities, as shown in Figures 3, 4, to retain more information. Figure 3 shows the impact of the number of principal components selected in PCA on the degree of information retention, and Figure 4 shows the correlation matrix of the four information combinations of active power, reactive power, current, and load rate in the PCA dimension reduction process.

3.1.2 Transformer abnormal inducement feature set

After the statistics of transformer fault cases, the abnormal transformer is found by inspection, online monitoring, live detection, power failure test, background alarm, light gas alarm, etc., even if effective measures are taken to avoid the expansion of the problem, or the defect continues to develop until the fault occurs. After sorting out the causes of transformer anomalies, the resulting feature set is shown in Table 1. If there is an abnormal cause of the transformer before the transformer failure, it can be marked

TABLE 1 Transformer abnormal inducement feature set.

Serial number	Abnormal inducement
1	External short circuit
2	Magazines or foreign objects
3	Vibration during long-term operation
4	Aging or wear
5	Damp or water
6	Overvoltage
7	External short circuit, extreme weather or earthquake
8	Extreme weather or earthquakes
9	External short circuit, aging or wear
10	External lead pull
11	DC bias

according to the corresponding serial number in Table 1. If there is no cause, it is marked as 0.

3.1.3 Feature extraction of long and short term memory network

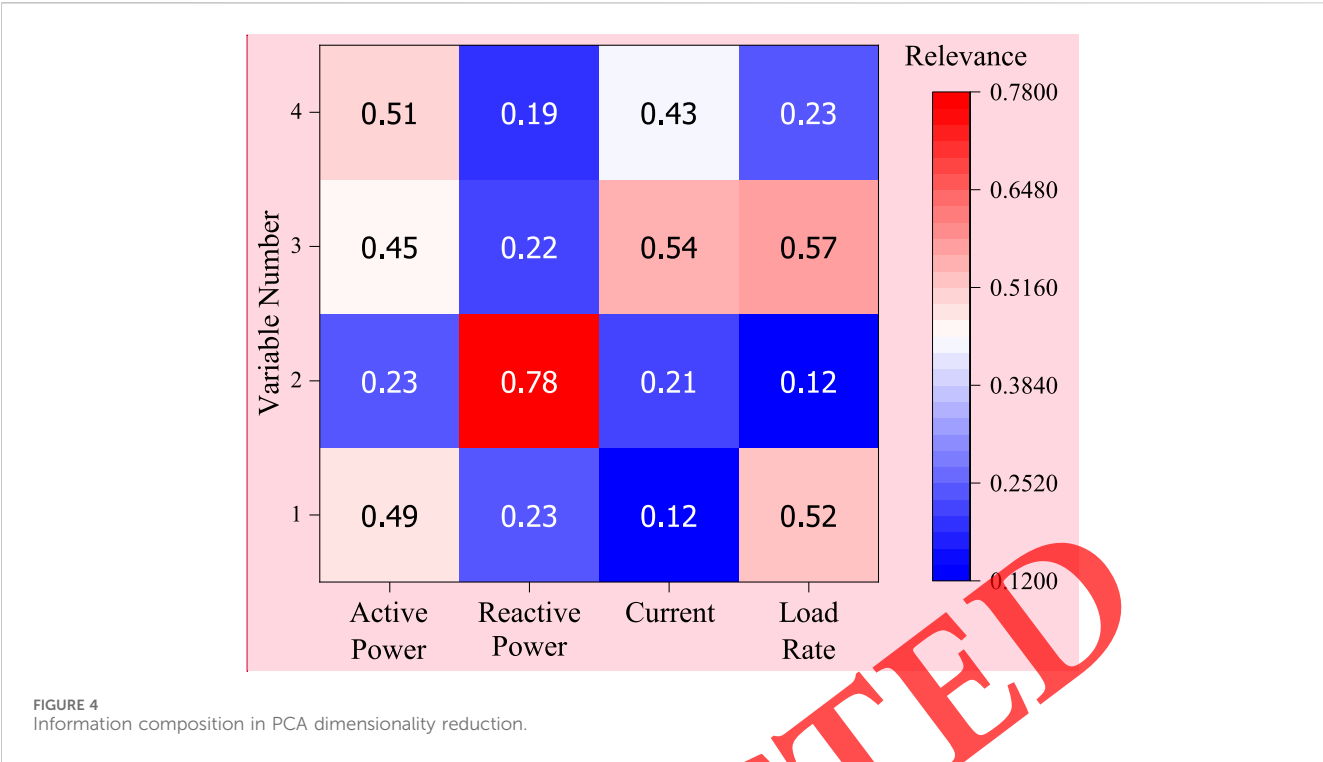
The model input six sets of 1 min sampling time series data of the same type of transformer in the training set. The data distribution statistics showed that the data changed little within 30 min. In order to optimize the running speed of the model, this paper resamples the time series data with a time interval of 30 min, determines the data label combined with the definition of the transformer running situation level, and converts this multivariate time series into supervised learning data mode. LSTM algorithm is used for training, and the feature extraction model of this type of transformer is obtained to predict the deterioration degree of transformer.

The optimal parameter learning rate $LR = 0.01$ of the model was selected by parameter tuning technique, and the time series data of other state samples in normal state were used for cross-validation. In the test set, the average root-mean-square error is 0.0053 and the average correlation coefficient is 0.89, indicating that the LSTM model has a good and stable prediction effect after adjustment.

3.2 Quantification of the impact of transformer alarm information

3.2.1 Quantification of the impact of alarm frequency

In the field of equipment monitoring business, there are five types of equipment alarm information: accident, abnormality, limit exceeding, displacement, and notification, which have the characteristics of strong real-time and large data volume. This article measures the impact of the five types of alarm information on the operation situation of transformers based on their severity, and establishes a judgment matrix as shown in Table 2. Using the Saaty1-9 scaling method (Zhang B. et al., 2020) to obtain the Analytic Hierarchy Process (AHP) judgment



matrix, obtain the judgment matrix, and introduce the Consistency Ratio (CR) for testing (McGilvray, 2021).

After calculation, the consistency check is satisfied, and the weight vector can be obtained as: $W = (0.43, 0.28, 0.19, 0.06, 0.03)$

alarm information in the same period in history. w_i indicates the weight of class i alarms. v is the coefficient of variation to describe the fluctuation of transformer operation situation; m indicates the number of alarms.

3.2.1.1 Alarm frequency year-on-year change indicator

Based on equipment monitoring and operation management experience, transformer alarm information has a clear seasonal pattern. Therefore, this article proposes a normalized indicator for the year-on-year change of alarm frequency statistics in the first quarter of this year to quantify the degree of deterioration trend of transformer operation. The calculation method is shown in Equation 1.

$$v = \frac{s}{\bar{f}_i} = \frac{\sqrt{\frac{1}{m-1} \sum_{i=1}^m [w_i (f_i - \bar{f}_i)]^2}}{\frac{1}{m} \sum_{i=1}^m w_i f_i} \quad (1)$$

where, f_i is the occurrence frequency of class i alarm information; \bar{f}_i is the average occurrence frequency of class i

3.2.1.2 Average comparison indicator of alarm frequency

According to the occurrence frequency and recurrence situation, alarm information can be classified into three types: normal, frequent, and not repeated for a long time. Different index calculation methods should be established for three different alarm signals.

For normal alarm signals, there should be a timely return signal after the action signal is sent. The calculation method is as follows:

$$A_1 = \sum_{i=1}^6 \frac{n_i}{N} w_i \quad (2)$$

where, A_1 indicates a normal alarm signal indicator. n_i is the number of times that class i alarm signals occur in the recent period. N indicates the total number of times that class i alarm signals occur in the recent period.

TABLE 2 Judgment matrix of five types of alarm information.

	Accident	Exception	Overlimit	Change	Notification
Accident	1	2	3	7	9
Abnormality	1/2	1	2	6	8
Limit exceeding	1/3	1/2	1	5	7
Displacement	1/7	1/6	1/5	1	3
Notification	1/9	1/8	1/7	1/3	1

For frequent alarm signals, it can be divided into two categories: short-term frequent large number of signals and long-term frequent action recurrence (Zhang et al., 2022). According to the provisions of the substation equipment monitoring information specification, signals that frequently exceed 10 in a day or return to more than 30 in a month are regarded as signal false positives caused by system problems, which can be reduced to the calculation in Formula 2, and the number of occurrences is counted as 1. Otherwise, calculate according to Equation 3.

$$A_2 = \frac{\beta'_i \beta''_i}{\sum_{i=1}^N \beta'_i \beta''_i} w_i, \beta'_i = \frac{n_i}{\sum_{i=1}^N n_i}, \beta''_i = \frac{T_i}{\sum_{i=1}^N T_i} \quad (3)$$

where, A_2 is a frequent alarm signal indicator; β'_i and β''_i are normalized indexes of frequency and duration, respectively. T_i indicates the duration of Class i frequent alarm signals.

The calculation method of the long time non-return signal and the frequent signal are consistent with Equation 3, and the signal is quantified from the two perspectives of frequency and duration.

3.2.1.3 Impact factors based on alarm frequency

The influence factor ξ based on alarm frequency can be comprehensively quantified by two dimensionless indicators, the year-on-year change indicator ν of alarm frequency and the average comparison indicator A_p ($p = 1, 2, 3$), as shown in Equation 4.

$$\xi = \frac{0.1\nu + \sum_{p=1}^3 A_p}{3} \quad (4)$$

where A_3 is a signal indicator that has not returned for a long time.

The influence factor based on the alarm frequency is closely related to the transformer operating state. The alarm frequency is higher than the same period last year and the average level, indicating that the state health degree shows a gradual downward trend, so as to quantify the deterioration degree of the transformer operating state.

3.2.2 Quantification of overload effects

After comparing the load rate statistics before and after transformer faults, it was found that not all transformer faults occurred under heavy load or even overload conditions. For transformers with significant changes in load rate in a short period of time, even if the change is greater than twice the original load rate, there is a high probability of transformer failure even if the load rate is between 40% and 60%. When the transformer has not experienced heavy load, but the increase in load rate within 3 days is greater than 1 times, the fault probability is given as the quantitative impact indicator of overload based on the statistical law of fault events, as shown in Equation 5:

$$K = \frac{l}{L} \quad (5)$$

where, L is the total number of events in which the transformer's load rate increases by more than 1 times within 3 days; l is the number of events in L that have failed.

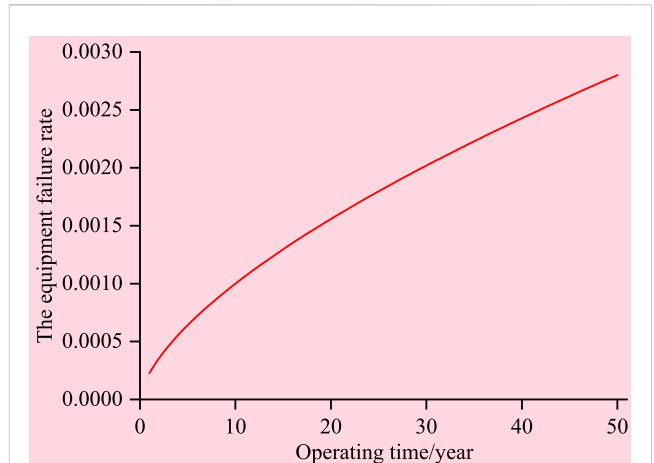


FIGURE 5
The equipment failure rate changes with the operating time.

3.3 Analysis of the influence of equipment operating life

3.3.1 Equipment aging model based on operating years

Transformers inevitably experience aging during operation. Even if transformers with different operating years are in the same state, the probability of failure is not always the same. The equipment failure rate function caused by the aging of its components during the operation of transformers can be fitted by a Weibull distribution model (Huang et al., 2022), as shown in Equation 6.

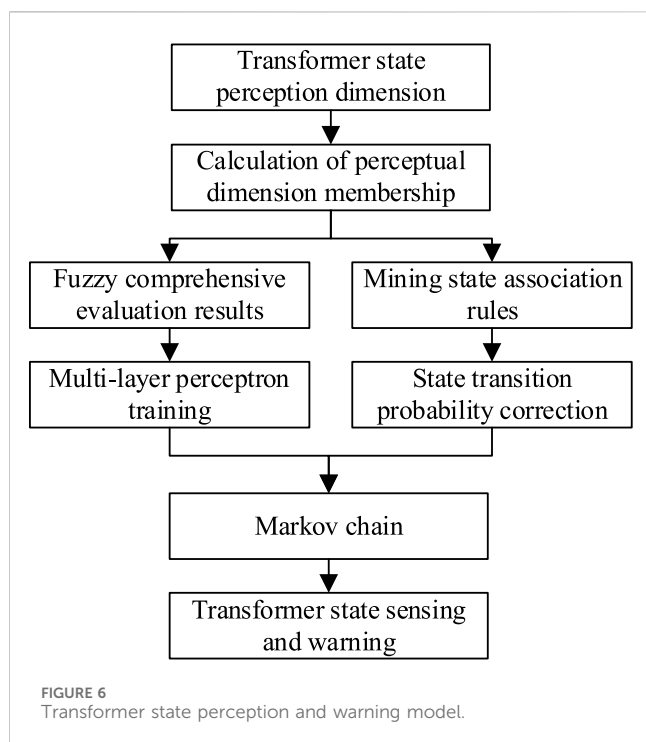
$$\gamma(t) = \frac{\beta}{\eta} \left(\frac{t}{\eta} \right)^{\beta-1} \quad (6)$$

where, β and η are the shape parameters and scale parameters of Weibull distribution model respectively, where η is also called the characteristic life of the device. τ indicates the operating life of the device.

According to statistical analysis, n oil-immersed transformers are collected, and their operating years, the number of exposed faults and the number of decommissioned components are counted. The failure rate should be the ratio of the number of decommissioned components and the number of exposed faults under the current time point (operating years), and the failure data can be obtained. According to different equipment conditions, Weibull parameters of 220 kV oil-immersed transformer are determined as follows: $\beta = 1.64$, $\eta = 224.15$. The curve showing the change in equipment failure rate over operating time is shown in Figure 5.

3.3.2 Modification of transformer aging probability based on regression factor

After the transformer is overhauled and maintained, its failure probability will change. In this paper, a component aging regression factor α is introduced to quantify the impact of transformer maintenance on the failure rate, where: after



equipment overhaul, α is 0.6; After minor equipment repair, α is 0.3. Transformer element aging regression factor α is calculated as follows:

After maintenance and repair, the probability of transformer failure will change. This article introduces the aging and return factor α of human group components to quantify the impact of transformer maintenance on failure rate. Among them, after equipment overhaul, α is taken as 0.6; After minor equipment repairs, α is taken as 0.3. The aging return factor α of transformer components is calculated as follows:

$$\alpha = 0.3[1 - 0.005(r_1 - 1)] + 0.6[1 - 0.005(r_2 - 1)] \quad (7)$$

where, r_1 and r_2 are the times of minor and major repairs of the transformer respectively.

4 Transformer situation warning based on transfer probability calculation

In order to achieve real-time control of transformer situation, calculate the transition probability from this state to another state, and use the transition matrix- Norms are used as warning indicators to achieve early warning of transformer situations. This article introduces the fuzzy comprehensive evaluation results as prior knowledge, trains a multi-layer perceptron model, and mines the association rules between transformer states. The transformer state transition matrix is calculated, and based on the initial state information of the transformer, the next state of the transformer is predicted. From this, the transformer state perception and warning model is obtained as shown in Figure 6.

4.1 Calculation of transformer state transition probability

The transition probability under the initial state of good state S1 is solved: In this paper, the relative deterioration degree of the transformer in three evaluation dimensions is quantitatively calculated, and the fuzzy evaluation results based on expert experience obtained by the method of literature (Wang and Zhao, 2020) are used as the prior knowledge of the multi-layer perceptron model, and the multi-layer perceptron model is trained with the input and the running situation level as the label In Softmax layer, the solution model of transformer operating situation level reliability is established. The classification result of this model is the possibility of the next state obtained by predicting the future state of the transformer, that is, the transition probability when the initial state is good state S1.

The initial state is general state S2, and the transition probability is solved. The transformers with an initial state of S2 all have abnormal inducement, or the relative deterioration degree of a certain evaluation dimension is greater than 0.6 considering the characteristics of operation years and operating environment, etc., and are transferred to the situation that the monitoring personnel pay special attention to. Therefore, compared with the good state, the abnormal inducement of the transformer can be returned to the good state after being eliminated by maintenance. In other cases, it is possible to maintain the normal state or transfer to the state S3 or S4. According to the definition of the transformer operating situation level, the first two evaluation dimensions are the main indicators for evaluating the general state. Therefore, in step 1), the correction factor team μ is introduced to correct the transition probability by reducing the evaluation weights of the first two dimensions. If the number of maintenance is less than 1, μ is 1; otherwise, μ is 0.5.

Calculation of transfer from abnormal state S3 to critical state S4. When the transformer is in an abnormal state, such small defects can be found in time through inspection or monitoring information. After statistical transformer fault cases, abnormalities are found in the transformer by inspection, online monitoring, live detection, power failure test, non-power protection alarm, etc., and even if effective measures are taken in time to avoid the expansion of the problem, or defects continue to develop until the fault occurs. This shows that when the transformer is in an abnormal state, if the small defect is not found and eliminated in time, it deteriorates and leads to the fault state, and there is an obvious association rule between the two states.

Support SD and confidence C are important indicators used to measure the association between condition item X and target item Y in association rules. Support SD is the number of events in the entire data set that contains both condition item X and target item, and confidence C is the ratio of the number of events that contain both condition item X and target item Y to the number of events that contain only condition item X. This paper quantifies the relationship between small defects and transformer fault events based on association rules. As one of the dimensions of transformer state perception, the rule form is as follows:

- (1) Transformer abnormal mode event set $X_{e,h} = \{\text{Item } h \text{ defect occurred in the component } e\}$.

TABLE 3 Fault confidence matrix from 2020 to 2023.

Serial number	Exception	Breakdown	2020	2021	2022	2023
1	Overload	Overheat	9.83	10.12	9.97	10.26
2	Abnormal oil pump system	Abnormal oil level /High oil temperature	17.36	16.64	18.13	15.27
3	Respirator abnormality	Damp fault	2.08	1.99	1.83	1.96
4	Seeping oil	Oil level anomaly	30.06	28.77	31.01	29.13
5	DGA exceedance	Discharge fault	7.32	10.02	9.71	9.36
6	Cooling system anomaly	High oil temperature	5.69	6.14	4.58	5.45

(2) Transformer failure mode event set $Y = \{\text{Component } e \text{ failure}\}$.

(3) Calculate confidence C , as shown in Equation 8:

$$C(X_{e,h} \Rightarrow Y_e) = \frac{SD(X_{e,h} \cup Y_e)}{SD(X_{e,h})} \quad (8)$$

where $SD(X_{e,h} \cup Y_e)$ and $SD(X_{e,h})$ are the numbers of datasets containing item sets $X_{e,h} \cup Y_e$ and $X_{e,h}$, respectively; Table 1 shows the statistics of abnormal mode event set X and failure mode event set Y .

According to the defect record data of a municipality in China from 2020 to 2023, the confidence matrix can be obtained, as shown in Table 3.

4.2 Transformer critical state warning

By calculating the transition probability of the transformer state, the maximum value of the transition probability in the row vector of the corresponding state in the transformer state transition matrix is taken as the next state predicted by the model. Based on the time span of three evaluation dimensions, the next state of the transformer and the transition probability between states can be predicted 5 h ahead. This article takes the 0-norm of the critical state vectors in the transformer state transition matrix as the measurement index of the early warning model, as shown in Equation 9.

$$\|\lambda_{i4}\|_{\infty} = \max_i |\lambda_i| \quad (9)$$

where, $i = 1, 2, 3, 4$; λ is the probability of transitioning from state S_i to state S_4 .

If the state transfer matrix of a transformer is $\|\lambda_{i4}\|_{\infty} \geq \min b_4 = 0.7$, an early warning will be issued to the monitoring personnel in time and on-site staff will be arranged to conduct inspections.

5 Case analysis

The experimental section of this article uses the anomalies and failure modes recorded during the operation of the 220 kV transformers in the fault log of a certain city in China from 2020 to 2023. The dataset is organized and outliers are removed to obtain a sample library of transformer status levels. The

evaluation index of the transformer state perception and early warning model based on Markov chain is selected as the overall prediction accuracy to verify the performance of the model, as shown in Equation 10. The overall prediction accuracy can accurately measure the consistency between the predicted results and the actual results in the entire sample set, and is suitable for verifying the universality of the algorithm model under sufficient sample library conditions.

$$\rho = \frac{q}{Q} \times 100\% \quad (10)$$

where, Q is the total number of samples; q is the number of samples whose model results are consistent with the actual running situation level.

Evaluate the performance of the model using k-fold cross validation based on samples from four state levels in the sample library. Randomly divide the samples into four groups, and perform a validation set for each subset of data. The remaining subset data in the $k-1$ group is used as the training set for overall prediction accuracy validation. The prediction performance validation results are shown in Table 4; Figure 7. Table 4 shows the accuracy of the Markov chain-based transformer state awareness warning model prediction results in four series, and Figure 7 is a visualization of the data in Table 4. From the charts, it can be seen that as the severity of transformer failures increases, the accuracy of the predictions decreases. However, the model is very accurate in predicting the Good state, and overall it can achieve an accuracy rate of about 93%.

Based on the average value of the four validation sets, the overall prediction accuracy of the transformer state sensing and early warning model based on Markov chain can reach 93.37%.

In order to further explain the practical application effect and specific calculation process of the transformer state perception and early warning model based on Markov chain proposed in this paper, the 2 # transformer of a 220 kV substation in a municipality directly under the central Government was taken as an example. The transformer had a high oil temperature alarm in June 2022, and the operation situation level was critical.

5.1 Feature extraction of operational data

Taking the 5 h before the fault of the 2 # transformer as the base point, a time series data group with a duration of 3 days was

TABLE 4 Prediction accuracy of transformer state sensing and early warning model based on Markov chain.

Serial number	State level	Good	General	Abnormal	Critical	Overall prediction accuracy (%)
1	The number of samples for the verification set	180	130	56	30	93.94
	The number of samples correctly predicted	179	123	49	21	
2	The number of samples for the verification set	180	130	56	30	93.18
	The number of samples correctly predicted	178	121	50	20	
3	The number of samples for the verification set	180	130	56	30	92.93
	The number of samples correctly predicted	177	118	51	22	
4	The number of samples for the verification set	180	130	56	30	93.43
	The number of samples correctly predicted	179	120	50	21	

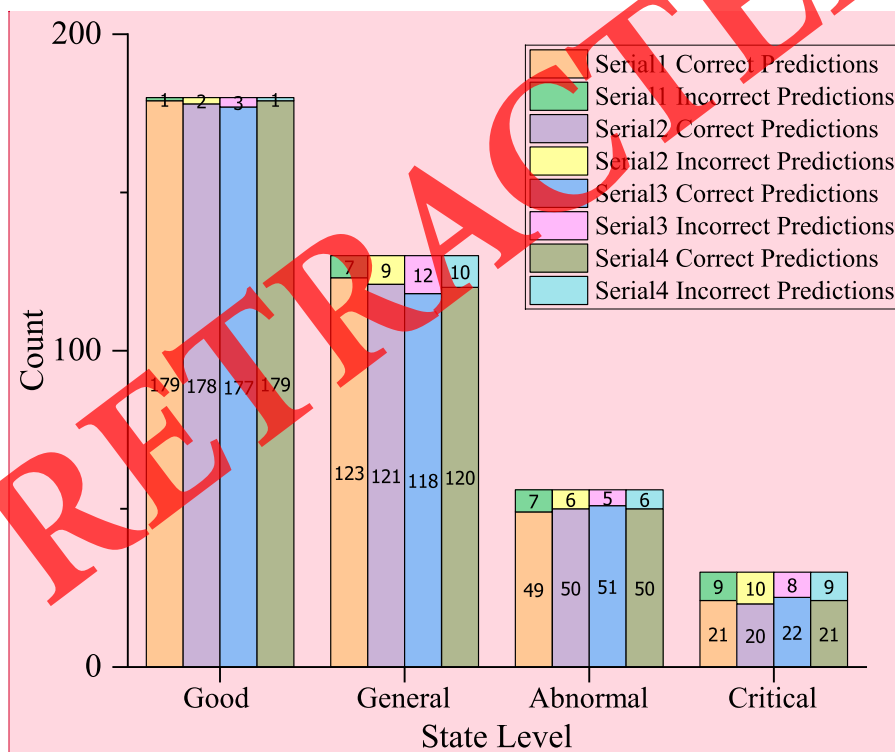


FIGURE 7

The count of correct predictions and incorrect predictions in each group.

extracted and constructed. There was no abnormal cause feature before the fault of the transformer, and the voltage exceeded the limit in the alarm term. The time series data group was resampled to 30 min and input into the previously trained LSTM feature extraction model, and the maximum value of the predicted defect label was 0.86 as the extracted running data feature value.

5.2 Quantification of alarm frequency and overload impact

After traversing the power transmission and transformation defect logs, there are more than 4,000 transformer related alarm data in this year, of which 471 are accident data. In addition to the recent 10 times of displacement signals of the oil pump system, the

transformer has exceeded the current limit for a duration of less than 1 min, and no other serious alarm signals of exceeding the limit or above have occurred. Therefore, from Equations 1–4: $\xi \approx 0$. The overload situation of the transformer can be statistically obtained according to the measurement data, and the transformer does not appear heavy, but the increase of the load rate of the transformer within 3 days before the failure is more than 1 times, that is, the load rate is 2 times the usual average. Therefore, we take $K = I/L = 54/131$.

5.3 Analysis of operating years

The transformer was put into service on 28 December 2012. There was no major repair record before, and all minor repairs were carried out during routine inspection. The last regular inspection was on 16 March 2021, with a total of five minor repair records, which can be obtained by Formulas 11, 12:

$$\alpha = 0.294 \quad (11)$$

$$\gamma(13.333 \times 0.706) = 9.619 \times 10^{-4} \quad (12)$$

In conclusion, the three evaluation dimensions of 2 # transformer in the characteristics of the value of $(9.619 \times 10^{-4}, 0.86, 0.226)$, based on the fuzzy comprehensive evaluation method can get corresponding to the four state probability for $(0.2541, 0.0860, 0.1124, 0.4965)$. These seven data are the input values of the multi-layer perceptron.

Since the operation characteristic of the transformer is 0.86, and there are no other small defects in the transformer at this time, there is no on-site inspection, so the transfer probability correction factor $\mu = 1$, and the state of the transformer is transferred from S2 to S4. The transfer matrix is calculated from the output results of the pre-trained multi-layer perceptron model, as shown in Equation 13, which proves that the transformer may fail after 5 h, meets the early warning conditions, and can realize timely warning to the monitoring personnel.

$$P = \begin{bmatrix} 9.216 \times 10^{-10} & 5.543 \times 10^{-6} & 5.409 \times 10^{-4} & 0.979 \\ 9.216 \times 10^{-10} & 5.543 \times 10^{-6} & 5.409 \times 10^{-4} & 0.979 \\ 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \end{bmatrix} \quad (13)$$

6 Conclusion

This article establishes a transformer state perception and early warning model based on the Markov chain principle. From the perspective of mechanism analysis and data-driven combination, three perception dimensions of transformer operation status are established based on multi-source data. Fuzzy comprehensive evaluation results are introduced into the multi-layer perceptron model, and a data-driven model based on prior knowledge is established. The association rules between state levels are mined,

and the state transition matrix is calculated to determine the next state of the transformer. Transformer state early warning indicators are also established. Taking the critical state case of transformer 2 # in a 220 kV substation in a certain municipality in 2022 as an example, a calculation analysis was conducted. A transformer status warning model was established to achieve the warning function under critical state of the transformer, effectively reminding dispatch personnel of the degree of transformer danger and arranging on-site personnel for inspection in a timely manner. In the future, the model can be further improved and expanded to cope with more complex operating environments and equipment failures in power systems.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding authors.

Author contributions

WW: Writing–original draft, Writing–review and editing. CR: Writing–original draft, Writing–review and editing. CY: Writing–review and editing. ZX: Writing–review and editing. XY: Writing–review and editing.

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Conflict of interest

Authors WW, CR, CY, ZX and XY were employed by Ordos Power Supply Branch of Inner Mongolia Power (Group) Limited Liability Company.

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References

- Abbasi, A. R. (2022). Fault detection and diagnosis in power transformers: a comprehensive review and classification of publications and methods. *Electr. Power Syst. Res.* 209, 107990. doi:10.1016/j.epsr.2022.107990
- Ausmus, J., de Carvalho, R. S., Chen, A., Velaga, Y. N., and Zhang, Y. (2019). "Big data analytics and the electric utility industry," in *2019 international conference on smart grid synchronized measurements and analytics (SGSMA)*, 1–7. doi:10.1109/SGSMA.2019.8784657

- Bai, J., Cong, P., Yu, L., Song, D., Sun, S., Han, X., et al. (2021). "Research on transformer fault diagnosis method based on principal component analysis and grey correlation analysis," in *2021 IEEE international conference on power, intelligent computing and systems (ICPICS)* (IEEE), 508–510. doi:10.1109/ICPICS52425.2021.9524278
- Enjavimadar, M., and Rastegar, M. (2022). Optimal reliability-centered maintenance strategy based on the failure modes and effect analysis in power distribution systems. *Electr. Power Syst. Res.* 203, 107647. doi:10.1016/j.epsr.2021.107647
- Fahim, A., Chowdhury, M. A., Alam, M. F., Elahi, F., Shourov, E. C., and Hasan, M. (2021). "Smart transformer theft protection and maintenance monitoring system," in *2021 2nd international conference on robotics, electrical and signal processing techniques (ICREST)*, 607–612. doi:10.1109/ICREST51555.2021.9331157
- Gashteroodkhani, O. A., Majidi, M., and Etezadi-Amoli, M. (2020). A combined deep belief network and time-time transform based intelligent protection Scheme for microgrids. *Electr. Power Syst. Res.* 182, 106239. doi:10.1016/j.epsr.2020.106239
- Horalek, J., and Sobeslav, V. (2023). Security baseline for substation automation systems. *Sensors* 23 (16), 7125. doi:10.3390/s23167125
- Hou, Z., Sun, X., Ju, Z., Li, Z., Niu, Q., and Liu, S. (2021). Design of the monitoring system for power distribution area by clean energy intelligent integration terminals. *IOP Conf. Ser. Earth Environ. Sci.* 804 (3), 032051. doi:10.1088/1755-1315/804/3/032051
- Huang, L., Lu, D., Zeng, W., and Zhou, Q. (2023). Pt-doped HfS₂ monolayer as a novel sensor and scavenger for dissolved gases (H₂, CO₂, CH₄, and C₂H₂) in transformer oil: a density functional theory study. *Langmuir* 39 (36), 12920–12930. doi:10.1021/acs.langmuir.3c02110
- Huang, W., Shao, C., Dong, M., Hu, B., Zhang, W., Sun, Y., et al. (2022). Modeling the aging-dependent reliability of transformers considering the individualized aging threshold and lifetime. *IEEE Trans. Power Deliv.* 37 (6), 4631–4645. doi:10.1109/TPWRD.2022.3152745
- Jia, L., Zhang, Y., Feng, W., Li, B., and Zhou, Q. (2023). Quantitative recognition of electrical parameters of transformer oil based on nondestructive ultrasound and the combined KPCA-WOA-Elman neural network. *Sensors Actuators A Phys.* 363, 114764. doi:10.1016/j.sna.2023.114764
- Li, B., Zhou, Q., Liu, Y., and Chen, J. (2022). A novel nondestructive testing method for dielectric loss factor of transformer oil based on multifrequency ultrasound. *IEEE Trans. Dielectr. Electr. Insulation* 29 (5), 1659–1665. doi:10.1109/TDEI.2022.3190821
- McGilvray, D. (2021). *Executing data quality projects: ten steps to quality data and trusted information (TM)*. Academic Press.
- Mharakurwa, E. T. (2022). In-service power transformer life time prospects: review and prospects. *J. Electr. Comput. Eng.* 2022 (1), 1–20. doi:10.1155/2022/9519032
- Mitiche, I., McGrail, T., Boreham, P., Nesbitt, A., and Morison, G. (2021). Data-driven anomaly detection in high-voltage transformer bushings with lstm auto-encoder. *Sensors* 21 (21), 7426. doi:10.3390/s21217426
- Peng, R., Zeng, W., and Zhou, Q. (2023). Adsorption and gas sensing of dissolved gases in transformer oil onto Ru₃-modified SnS₂: a DFT study. *Appl. Surf. Sci.* 615, 156445. doi:10.1016/j.apsusc.2023.156445
- Prasajo, R. A., Putra, M. A. A., Apriyani, M. F., Rahmanto, A. N., Ghoneim, S. S., Mahmoud, K., et al. (2023). Precise transformer fault diagnosis via random forest model enhanced by synthetic minority over-sampling technique. *Electr. Power Syst. Res.* 220, 109361. doi:10.1016/j.epsr.2023.109361
- Ravindran, V., Ponraj, R., Krishnakumar, C., Ragunathan, S., Ramkumar, V., and Swaminathan, K. (2021). "IoT-based smart transformer monitoring system with raspberry Pi," in *2021 innovations in power and advanced computing technologies (i-PACT)*, 1–7. doi:10.1109/i-PACT52855.2021.9696779
- Soni, R., and Mehta, B. (2021). Review on asset management of power transformer by diagnosing incipient faults and faults identification using various testing methodologies. *Eng. Fail. Anal.* 128, 105634. doi:10.1016/j.engfailanal.2021.105634
- Tang, S., Chen, W., Jin, L., Zhang, H., Li, Y., Zhou, Q., et al. (2020). SWCNTs-based MEMS gas sensor array and its pattern recognition based on deep belief networks of gases detection in oil-immersed transformers. *Sensors Actuators B Chem.* 312, 127998. doi:10.1016/j.snb.2020.127998
- Tao, J., Xiao, Z., Li, Z., Wu, J., Lu, R., Shi, P., et al. (2021). Dynamic event-triggered state estimation for Markov jump neural networks with partially unknown probabilities. *IEEE Trans. Neural Netw. Learn. Syst.* 33 (12), 7438–7447. doi:10.1109/TNNLS.2021.3085001
- Trappey, A. J., Trappey, C. V., Ma, L., and Chang, J. C. (2015). Intelligent engineering asset management system for power transformer maintenance decision supports under various operating conditions. *Comput. Industrial Eng.* 84, 3–11. doi:10.1016/j.cie.2014.12.033
- Wang, G., Liu, Y., Chen, X., Yan, Q., Sui, H., Ma, C., et al. (2021). Power transformer fault diagnosis system based on Internet of Things. *Eurasip J. Wirel. Commun. Netw.* 2021, 21–24. doi:10.1186/s13638-020-01871-6
- Wang, J., Zhang, X., Zhang, F., Wan, J., Kou, L., and Ke, W. (2022). Review on evolution of intelligent algorithms for transformer condition assessment. *Front. Energy Res.* 10, 904109. doi:10.3389/fenrg.2022.904109
- Wang, N., and Zhao, F. (2020). An assessment of the condition of distribution network equipment based on large data fuzzy decision-making. *Energies* 13 (1), 197. doi:10.3390/en13010197
- Yao, W., Xu, Y., Qian, Y., Sheng, G., and Jiang, X. (2020). A classification system for insulation defect identification of gas-insulated switchgear (GIS), based on voiceprint recognition technology. *Appl. Sci.* 10 (11), 3995. doi:10.3390/app10113995
- Zhang, B., Li, C. C., Dong, Y., and Pedrycz, W. (2020b). A comparative study between analytic hierarchy process and its fuzzy variants: a perspective based on two linguistic models. *IEEE Trans. Fuzzy Syst.* 29 (11), 3270–3279. doi:10.1109/TFUZZ.2020.3018110
- Zhang, C., He, Y., Du, B., Yuan, L., Li, B., and Jiang, S. (2020a). Transformer fault diagnosis method using IoT based monitoring system and ensemble machine learning. *Future gener. Comput. Syst.* 108, 533–545. doi:10.1016/j.future.2020.03.008
- Zhang, D., Chu, Z., Gui, Q., Wu, F., Yang, H., Ma, Y., et al. (2023). Transformer maintenance decision based on condition monitoring and fuzzy probability hybrid reliability assessment. *IET Generation, Transm. Distribution* 17 (4), 976–992. doi:10.1049/gtd.2.12718
- Zhang, Y., Shi, X., Zhang, H., Cao, Y., and Terzija, V. (2022). Review on deep learning applications in frequency analysis and control of modern power system. *Int. J. Electr. Power & Energy Syst.* 136, 107744. doi:10.1016/j.ijepes.2021.107744